Investigating the Impact of Real-Time Thermal Ratings on Power Network Reliability

David M. Greenwood, *Student Member IEEE*, Phil C. Taylor, *Senior Member IEEE*

Abstract— **Real-Time Thermal Rating (RTTR) is a smart grid technology that allows electrical conductors to operate at an enhanced rating based on local weather conditions. RTTR also provides thermal visibility of the network, making system operators aware if the actual rating drops below the static seasonal rating. This paper investigates how using these enhanced, variable ratings affects power network reliability. A methodology has been developed to assess network reliability with variable conductor ratings. The effect of failures and uncertainties in the RTTR system are also considered, and the effect of the correlation between conductor ratings due to common weather conditions is built into the model. State sampling and sequential Monte Carlo simulations are used to estimate the reliability of the RBTS 6-bus test network. At low loading levels the RTTR appears to reduce network reliability, but actually illustrates occasions when the existing ratings are being unknowingly infringed. For higher loading the network reliability is significantly improved by the use of RTTR, with reductions in loss of load expectation of up to 67%.**

Index Terms— Power system planning, Power system reliability, Transmission lines, Smart grids

I. Introduction

REAL-TIME THERMAL RATING is a smart grid technology which allows electrical conductors to operate at an enhanced rating based on local weather conditions. Conventionally overhead lines are given a fixed rating based on a conservative set of weather conditions [1, 2]. The actual rating is dependent on the local wind speed, wind direction, ambient temperature and solar radiation, and is often significantly higher than the seasonal static rating [3]. A number of systems have been developed to exploit this additional capacity [4-6].

This paper describes a methodology to evaluate the impact that of using this enhanced, variable rating on network reliability. Energy targets such as the 80% reduction in CO_2 emissions by 2050 target in the EU [7], will cause an increase in electricity demand as transport and heating are electrified. This could cause the presently reliable transmission and distribution systems to become unreliable and need significant reinforcement. RTTR, as part of a larger suite of smart grid technologies, could eliminate or reduce the need for new conductors while giving network operators more information about the state of the system.

Although RTTR allows conductor ratings to be set in real time, this paper deals with the technology from an offline planning perspective. While on first inspection this may seem counter intuitive, it is essential to be able to understand the impact of a new technology before it is deployed on a real network. The methods described allow the impact of the variable ratings on network reliability to be quantified at the planning stage. Thorough calculations can be performed at this stage without the time constraints that may be present during operation.

The archival value of this paper lies in the adaptation of established reliability analysis techniques to work with the upcoming RTTR technology, coupled with a quantification of the benefits RTTR can provide to network reliability. Further to this, RTTR’s deployment is dependent on proper understanding of the accuracy and reliability of the RTTR system; this paper demonstrates the effect of the uncertainty and reliability of RTTR on system reliability.

II. Power System Reliability

Power system reliability has always been important to network operators. Since the advent of computing power, more complex solutions, both analytical and Monte Carlo (MC) based, have become available. There are two problems to be solved within power system reliability; generation adequacy, whether there is sufficient generation to meet demand and transmission adequacy, whether there is sufficient transmission capacity to connect generation to load [8]. Transmission systems are concerned with both problems, while distribution networks are only concerned with transmission adequacy. That being said, generation at lower voltages can be used to assist in transmission adequacy [9]. Since RTTR provides a benefit to transmission adequacy, only that was considered in this work.

Network reliability can be quantified in different ways. Loss of Load Expectation (LOLE) is the likelihood that the load in the system cannot be adequately supplied [8]. Loss of Energy Expectation (LOEE) goes further by assessing the deficit between the load and the supply. Although it has more physical significance than LOLE, it has less flexibility and has been less widely applied [8].

This work was supported by EPSRC, Scottish Power Energy Networks and Astrium GEO-Information Services.

D. M. Greenwood is with the School of Electrical and Electronic Engineering, Newcastle University, Newcastle Upon Tyne, NE1 7RU, UK (email: d.m.greenwood2@ncl.ac.uk).

P. C. Taylor is with the Newcastle Institute for Research on Sustainability (NIReS), Devonshire Building, Newcastle University, Newcastle Upon Tyne, NE1 7RU, UK (email: phil.taylor@ncl.ac.uk).

A. Probabilistic Reliability Assessment

Power systems are large and complex; consequently they can occupy many different states during operation. This large state space makes analytical state space enumeration, where the probability and consequence of each state is evaluated, difficult and time consuming. MC simulations offer a way to explore this state space by simulating a large number of random input states to assess system behavior.

MC simulations can take various forms. For this application one option is state sampling MC [10, 11], where each input variable is assigned a probability distribution. Samples from these distributions are then used to perform a large number of calculations to explore the state space. This method is simple, but does not account for any time dependencies within the model. The sequential MC simulation [12, 13] keeps this time dependency intact, but at the cost of greater computational resources and complexity. A method for pseudo sequential MC simulation was proposed [14] where states are sampled randomly from a time series, but on occasions where the system was not adequate the duration of this inadequacy was examined by looking at the appropriate section of the time series.

A key difficulty in evaluating the impact of RTTR on system security is the correlation structure between the ratings of the lines in the network. Networks cover a wide geographical area, so overhead lines which are directly connected will have highly correlated ratings, while lines which are more remote from one another will have weakly correlated ratings. This implies that stronger correlation will be present in meshed networks than radial networks, since in meshed networks a large number of conductors cover a smaller geographical area. The correlation between conductors in transmission networks will generally be lower than those in distribution networks, because the transmission network spans a larger geographical area. In all cases, the terrain local to the conductors will have an impact on these correlations. The effect of wind speed correlation on the reliability provided by wind generation was investigated by [15] and a methodology for incorporating these correlations into the MC simulation was developed. The method used a genetic algorithm to ensure the sampled variables corresponded to a previously selected correlation between wind sites. The methodology used an Auto-Regressive Moving Average (ARMA) model of wind speed [16]. This allowed a synthetic data set much larger than the real data set available to be used in a sequential MC simulation. The paper concludes that multiple independent wind farms provide a higher contribution to network security than a single wind farm, or multiple wind farms in the same wind regime.

This concept is important for assessing the impact of RTTR on reliability, though the effect of the correlations may be different. The correlation between the ratings of lines must be accounted for in any model of network reliability incorporating RTTR.

B. Novel Reliability Assessment Methodologies

The MC based approach has come under criticism in recent years because of its time and computation requirements. Consequently new methods have been proposed which attempt to provide the same level of detail as MC at a reduced computational cost. Several of these approaches, which attempt to enumerate the probability states efficiently, were considered for this application [17-20].

Unfortunately these approaches are not well suited to the RTTR application. The variable conductor ratings mean that each conductor has many states representing different rating levels. This vastly increases the number of low probability states, making state enumeration more intensive. The number of states could be reduced by breaking the rating of the line into a small number of discrete states, but this would lead to a loss of detail in the results. The complex correlations between the conductor ratings in the network are also difficult to assess using a state space method, but can be accounted for using a sequential MC simulation.

After investigating the available methods for assessing power system reliability, sequential Monte Carlo simulation seems most appropriate for the RTTR application. MC is an effective means of exploring a large number of low probability states [18], and sequential simulations allow the correlations between line ratings to be accounted for. The downside with MC is that long calculations are required. Because this work deals with network reliability from a planning perspective, time consuming calculations are acceptable.

C. Smart Grid Reliability

Implementing smart grid projects will have an impact on network security [21]. The consensus is that smart grids will rely heavily on IT and communications infrastructure [14, 21], and that the reliability of these components will heavily influence the reliability of the smart grid. It is clear that in assessing the impact of RTTR on power network reliability, the reliability of the RTTR technology must be taken into account.

III. Methodology

A. Overhead Line Reliability Model

The reliability of the overhead lines in this study was represented as a two state Markov process; an up state (available) and a down state (unavailable) [22]. The probability of being in the down state is given by:

$$P_{line} = \frac{MTTR}{MTTF + MTTR} = f\,\frac{MTTR}{8760} \qquad (1)$$

Where *MTTR* is mean time to repair, *MTTF* is mean time to fail (in hours) and f is the failure rate (failures per year). Transmission system reliability data were available [23].

B. Reliability Test Networks

In order to develop a methodology for assessing the reliability of an RTTR enabled network, a test case must be used. Probabilistic reliability analysis is more commonly performed on transmission networks, due to the high complexity and comparatively low impact of distribution networks on loss of load.

Various test networks are available. Figure 1 shows the RBTS [24] is a 6 bus, 9 transmission line system. This small network was used because it allowed results to be easily analyzed. The changes in power flows due to outages are obvious, so it is easy to see where RTTR is providing a benefit. The IEEE 14-bus, 24-bus and 39-bus networks were used to test the scalability of the method.

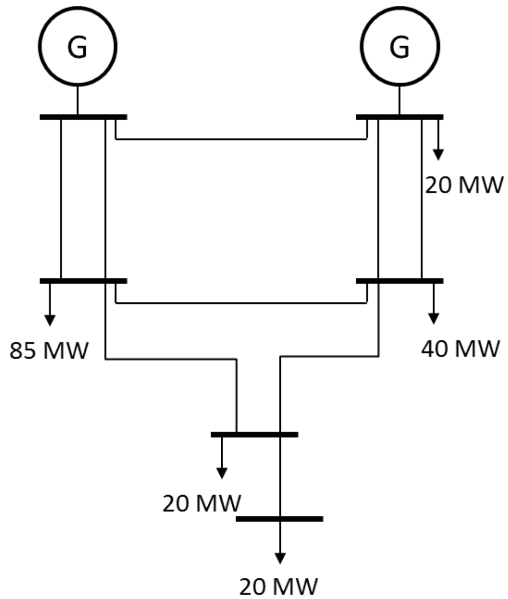

Figure 1: Diagram of the test network

C. State Sampling Simulations

State sampling Monte Carlo simulations are simple to perform. The different parameters in the model are represented by probability distributions. In each calculation, every parameter is represented by a random sample from these probability distributions. The model is then run a large number of times to effectively explore the state space. Reliabilities can be represented as a simple probability derived from the MTTF and MTTR, since the state sampling method does not use any kind of time series.

The line ratings were approximated by a normal distribution with μ=1.7 and σ=0.35 as a proportion of static rating. The load data were sampled from a simple load distribution curve. Since this study is concerned with the impact of RTTR on transmission adequacy the generation was considered to be perfectly reliable. The impact of RTTR on composite system reliability could be considered in a future study.

State Sampling studies gave reasonable results, but the impact of outage durations, the time domain behavior of the line rating and loading and the correlation structure between the line ratings were all of interest, and could only be properly represented by a sequential simulation.

D. Sequential Monte Carlo

Sequential MC was used to give a more complete and realistic representation of the system. Synthetic time series were used rather than PDFs, and a Markov model was used to represent the reliabilities.

To perform sequential MC studies, the existing sampling method for generating rating data was replaced with synthetic time series calculated using real data. An Auto Regressive Moving Average (ARMA) model was used to represent the ratings. Third order auto regressive and first order moving average models were used. The model was generated using the square root of the ratings data, since this provided a closer approximation to a normal distribution than the ratings themselves. The distribution used is dependent on the specific historical data, and an appropriately selected model will lead to more representative results.
The autoregressive model was of the form:

$$R_{(t)} = 1 + 1.47143R_{(t-1)} - 0.425698R_{(t-2)} - 0.0500508R_{(t-3)} - 0.825862\alpha_{(t-1)} \tag{2}$$

Where α is a random sample from a normal distribution with μ=0 and σ=1.216. The model is based on data from a RTTR trial site with a sampling rate of 5 minutes [4]. The thermal time constant of the overhead line is such that the rating must be updated every 5 minutes to ensure the conductor operates within the thermal limit [25]. One year of historical data was available, so the ARMA model was used to allow simulations of time periods greater than one year. Using ARMA models rather than using historical data directly also allowed investigation into the impact of different levels of correlation between the overhead line ratings on the overall network reliability. Load data were generated using a similar model. The model parameters were selected using historical load data. Again, the ARMA model used a normal distribution based on the square root of the load data, since this gave the best approximation to the data.

The PDFs used were evaluated in terms of the average root mean square error (ARMS) [26]:

$$ARMS = \frac{\sqrt{\sum_{i=1}^{N}(F_{Mod,i} - F_{Ref,i})^2}}{N} \tag{3}$$

Where $F_{Mod,i}$ and $F_{Ref,i}$ are the i^{th} values on the CDF curves of the fitting model and the reference respectively. N is the number of selected points which are chosen from the range of the CDFs within a certain interval. The historical data were used as the reference. The ARMS values for the models used in the analysis are shown in Table 1.

Parameter	*ARMS Error*
Rating	3.57%
Load	2.70%
Square Root of Rating	2.03%
Square Root of Load	0.70%

Table 1: Average Root Mean Square errors of the load and rating distributions

E. Correlated Rating Time Series

In a network, conductors at geographically close locations will have ratings which are correlated to one another in some way. Figure 2 shows correlations calculated using weather data from the UK. The weather data was used to calculate conductor ratings via the CIGRE overhead line model [27]. Two sets of weather stations were used; one set of tightly grouped stations, with a maximum spacing of 15km, and four stations spread across the UK with a maximum spacing of over 600km. The correlations were calculated using the Pearson product-moment correlation:

$$corr(X,Y) = \frac{cov(X,Y)}{\sigma_x\sigma_y} = \frac{E[(X-\mu_x)(Y-\mu_y)]}{\sigma_x\sigma_y} \tag{4}$$

Where *cov* is the covariance, *E* is the expectation; μ is the mean and σ is the standard deviation.

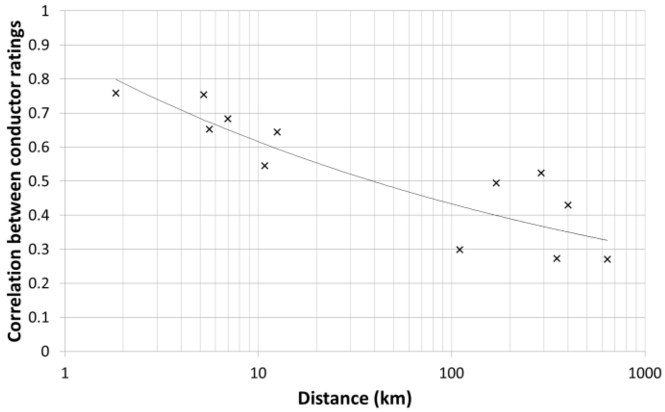

Figure 2: Plot of correlation between conductor ratings against distance between conductors

The results demonstrate that although the high correlation between the ratings of nearby conductors decays quickly with distance, there is still some correlation between conductors hundreds of kilometers apart. Conductor ratings are governed by weather conditions, and conductors hundreds of kilometers apart will still be affected by the same large scale weather phenomena.

These correlations must be represented in the model. The ARMA model used to represent the ratings uses a random number string as part of the moving average model. If these strings are specified with set correlations to one another, then the resulting ratings data will have a similar correlation [15].

Specified random number series can be generated using Cholesky decomposition [28]. This approach requires a positive definite matrix to be specified, where element (*a*,*b*) represents the desired correlation between conductors a and b (resulting in 1s on the leading diagonal, since this represents the correlation of a rating with itself). Cholesky decomposition is performed, to give the matrix U. A matrix of uncorrelated random numbers, R, can then be multiplied by U to give *Rc*, a matrix of correlated random numbers. This is shown in equation 5.

$$C = \begin{bmatrix} 1 & 0.75 & 0.60 & 0.75 & 0.60 & 0.75 & 0.45 \\ 0.75 & 1 & 0.75 & 0.75 & 0.75 & 0.6 & 0.60 \\ 0.60 & 0.75 & 1 & 0.75 & 0.65 & 0.75 & 0.60 \\ 0.75 & 0.75 & 0.75 & 1 & 0.75 & 0.75 & 0.60 \\ 0.60 & 0.75 & 0.75 & 0.75 & 1 & 0.75 & 0.75 \\ 0.75 & 0.60 & 0.75 & 0.75 & 0.75 & 1 & 0.75 \\ 0.45 & 0.60 & 0.60 & 0.60 & 0.75 & 0.75 & 1 \end{bmatrix} \quad (5)$$

$$R_C = RU \quad (6)$$

An example of this for the RBTS ratings is shown in equation 4 above. Conductors 1 and 6 and conductors 2 and 7 were assumed to have the same rating, so only seven sets of correlated ratings were generated. Figure 3 shows an example of this data. The correlations were checked against the desired values before the simulations were carried out. Alternatively the correlated random number series could be created through eigenvalue decomposition or using genetic algorithms [15].

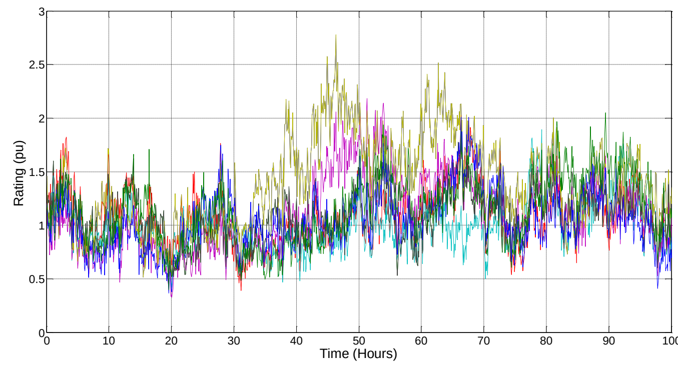

Figure 3: 7 sets of rating data with pre specified correlations

Load data were created using the same method; the correlation between all loads was set to 0.8.

The conductor reliability model was calculated ahead of time, with time series of data with each conductor in either the 0 (down) or 1 (up) state. A model was also included for the reliability of the RTTR system. When the RTTR system is in the 0 state, the conductor reverts to its static rating. This is a worst case assumption, since in operation some form of graceful degradation could be applied [29]. The MTTF and MTTR values for the conductors were taken from [24]. The RTTR system was assigned a MTTF of 3 months and a MTTR of 10 hours, though in reality these values would vary depending on which RTTR technology was implemented.

F. Uncertainty Quantification

In a real system, the operator will not have perfect information about the rating of the conductors. If weather based RTTR [4] is used, there are uncertainties in the measurement of weather parameters, the line rating model and using weather station data to estimate conductor ratings at an unobserved location. If a tension or sag monitoring solution [30] is used then there is uncertainty in the measurement of sag or tension, error in the model used to infer a rating from this data and further uncertainty because it is unlikely that every conductor span will be instrumented. If this methodology is to provide an accurate assessment of the benefits of RTTR then these uncertainties must be accounted for. Equation 6 shows an uncertainty model for RTTR, where e_{mod} is the uncertainty associated with the CIGRE ratings equations, e_{meas} is the uncertainty in weather or conductor rating measurements, e_{PDF} represents the difference between the assumed probability distribution and the true data, calculated using the ARMS error in section III, and e_{interp} is the uncertainty arising from calculating the rating of a conductor based on measurements that are some distance away.

$$E = f(e_{mod}, e_{meas}, e_{interp}, e_{PDF}) \quad (7)$$

This function was evaluated using a Monte Carlo model, using typical uncertainty values from RTTR proof of concept studies [4, 5] and the uncertainty in the CIGRE rating model [31]. The rating equations, along with randomly generated input errors, were used to calculate the distribution of errors is shown in Figure 4. The largest source of error is the interpolation error, which stems from the physical spacing of measurement equipment and the variability of weather conditions on relevant space scales. This could be alleviated by heavily instrumenting the network or by pre-identifying critical spans and instrumenting those areas.

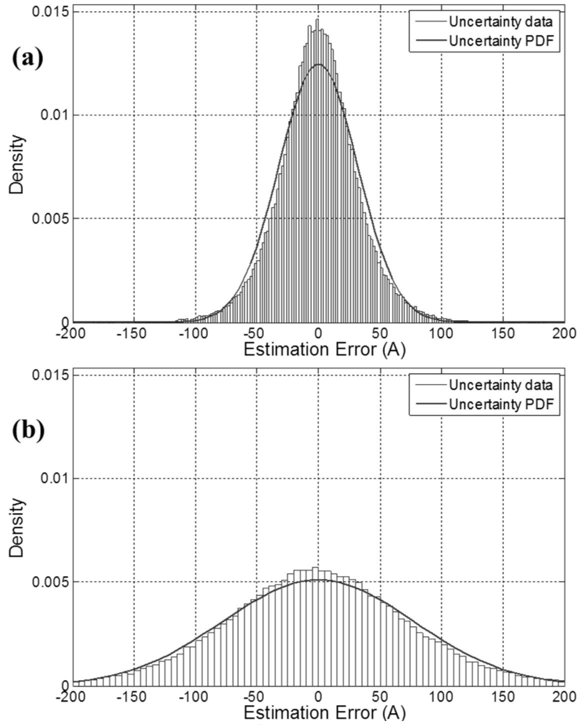

Figure 4: Probability distribution of the error in rating estimation

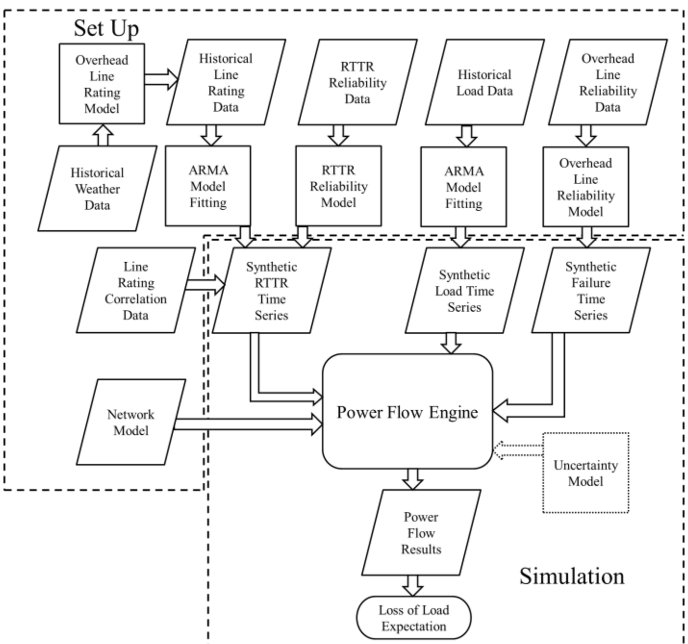

Figure 5: A Flow chart showing the complete methodology, broken into set up and simulation steps

Figure 4(a) shows the error distribution with an interpolation error of 0% (the error at the location of the measurement), while 4(b) shows the error distribution with a 10% interpolation error (equivalent to a distance of 1km from the measurement location).

The sequential simulation was run with different levels of rating uncertainty to see how this would affect the system reliability.

The complete methodology is shown in a flow chart in Figure 5. The method is broken up into set up and simulation steps.

IV. Results

A. System Behavior

The main goal of this paper is to produce a methodology to assess the impact of RTTR on transmission reliability. In order to do this it is important to first establish confidence that the methodology delivers a good representation of system behavior with and without RTTR.

Figure 6 shows 90 hours of data from one line from a simulation of the test network. The figure shows a failure of the RTTR system, where the rating reverts to the static value and a failure of the overhead line where the line flow drops to zero. This capacity is made up by the other lines in the network, which could cause them to exceed their static ratings. An outage on another conductor is also shown, leading to a rise in the current flowing through the observed line.

Figure 6 also illustrates the behavior of the line flow and the rating in a system using RTTR. On some occasions the RTTR drops below the static rating; having knowledge of this could help network operators make decisions during an outage to prevent damage to a conductor or a potential cascading failure. On other occasions the line flow goes above the static limit, but still stays well below the RTTR. This demonstrates the benefit of RTTR not just to reliability, but to network capacity.

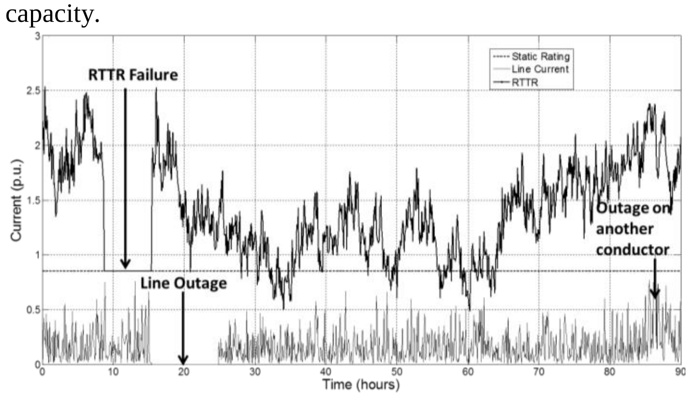

Figure 6: A plot of RTTR, static rating and line flow in amps, with an RTTR failure a line outage, the line flow exceeding the static rating and the RTTR dropping below the static rating all pictured

B. Reliability Indices

The network was assessed in terms of its LOLE for a variety of loading conditions using sequential MC simulations. Figure 7 shows the LOLE of the RBTS for different loading conditions. The load was increased uniformly taking the mean loading from 0.285pu up to 0.855pu. For low loading conditions the static rating appears to give a lower LOLE. This is an artifact from the calculation method used for overhead lines, and is effectively giving network operators a false sense of security. Conventionally lines are rated such that there is a low, but non-zero, probability of the actual rating being below the nominal rating.

At higher loading conditions the two data series diverge, with the RTTR providing a substantially lower LOLE. This is because often the high current flows required in the event of an outage can be supported by the enhanced capacity provided by RTTR, while using the static rating would require load to be shed or other corrective action to be taken.

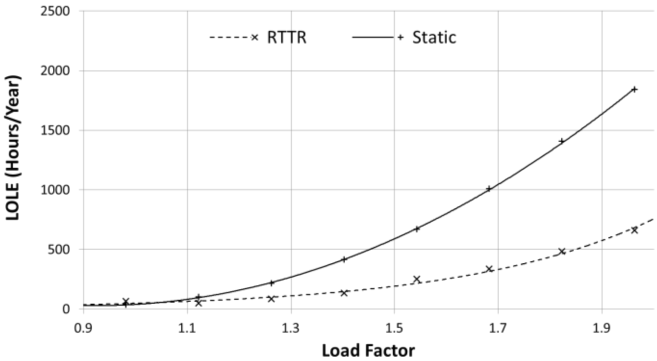

Figure 7: LOLE in hours per year for RTTR and static ratings at different network loading conditions

C. *Effect of Correlation*

More geographically dispersed networks will have a lower correlation between conductor ratings. Figure 8 shows the reliability of the network for different levels of correlation between conductor ratings, varying from complete independence to complete dependence.

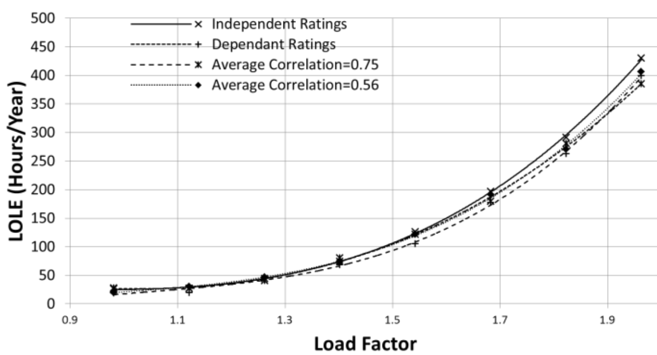

Figure 8: The results demonstrate that although the high correlation between the ratings of nearby conductors decays quickly with distance, there is still some correlation between conductors hundreds of kilometers apart.

The impact of correlation on reliability is small when compared with the overall improvement of using RTTR. The case with completely independent ratings yielded the lowest reliability. This is because there is greater variance between the ratings of lines within the network, leading to a higher likelihood of one line having a low rating and resulting in a loss of load. The effect of correlation increases with loading, because at higher loads reliability is more dependent on RTTR.

D. *Impact of Uncertainty*

Rather than using a confidence interval, for each step in the time series the LOLE was evaluate probabilistically.

$$LOL_{k,j} = P(R_{k,j} < i_{k,j}) \quad (8)$$

And from the concept of expectation:

$$LOLE = 1 - \frac{\sum_{k=1}^{m} \prod_{j=1}^{n} (1 - LOL_{k,j})}{m} \quad (9)$$

Where m is the number of iterations, n is the number of circuits, R is the line rating, i is the line current, j is the line number and k is the time step.

Figure 9 shows the impact of accounting for uncertainty on the perceived benefit. The uncertainty shown had a standard deviation of 30A, which corresponds to the error at the location of a sensor. As the distance from the sensor increased, the uncertainty increased considerably and consequently the LOLE was greater.

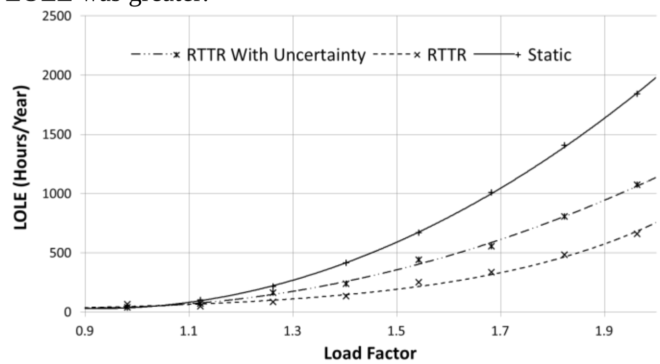

Figure 9: LOLE in hours per year for RTTR with and without uncertainty. While the uncertainty reduces the improvement in LOLE there is still a significant benefit.

With the uncertainty in the RTTR represented in the simulation there is still a benefit to reliability as loading increases. If a more accurate sensor or conductor thermal model were available, the LOLE would further decrease, approaching the benefit of the ideal RTTR system.

E. *Scalability*

The results presented so far used the 6 bus RBTS. Since real power systems are larger, it is important to ensure the method functions on larger networks and scales reasonably in terms of computational time. RTTR calculations were performed for the IEEE 14, 24 and 39-bus test networks to test the system at multiple voltage levels and to see how well the simulation scaled with network size.

No. of Buses	*Simulation Time (100,000 Iterations)*
6	53 minutes
14	58 minutes
24	72 minutes
39	80 minutes

Table 2: The impact of network size on simulation time

Table 2 shows that the simulation time scales well with network size. These simulations were performed on a desktop PC with an Intel i5 processor and 8 GB of RAM. A more powerful computer could reduce the computational times. Figure 10 shows the results of these simulations in terms of LOLE for the 14 and 24 bus network. The general trends are similar to that of the RBTS, with RTTR providing lower LOLE at higher load levels. However, the specific results depend on the network topology and loading conditions.

RTTR deployments are likely to only cover subsections of network [6], usually where power flow congestion, load growth or high penetrations of wind energy are a problem. Consequently, this analysis will be possible within a reasonable time frame.

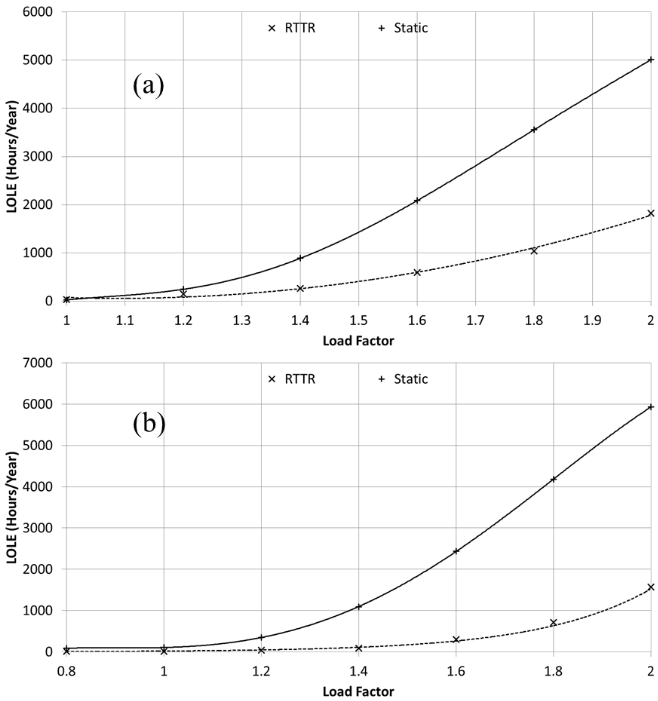

Figure 10: LOLE in hours per year for the (a) 14 and (b) 24 bus network with and without RTTR

V. Discussion

A. Holistic Smart Grid Approach

The results show that RTTR can give a substantial reduction in LOLE for heavily loaded networks. However the resulting LOLE is still higher than network operators would accept. Consequently it is clear that RTTR cannot allow a doubling of network capacity in isolation. However as part of a holistic smart grid deployment RTTR could allow substantial increases in network capacity at a lower cost than conventional reinforcement.

For example if RTTR was employed alongside energy storage and demand side response (DSR) it should be possible to maintain the same high levels of reliability the network enjoys today. When the RTTR is high, energy could be transferred into storage facilities, and when the rating is low the additional capacity could be made up through storage. If this was not sufficient, DSR could be used to ensure no customers are disconnected. Distributed generation could also be used to compensate during periods of low rating.

B. Financial Benefits

One of the incentives for network operators to connect distributed generation is that it can defer investment in new conductors [32]. RTTR can offer a similar financial benefit. A scheme implemented by Scottish Power Energy Networks in the UK [33] suggests that implementing RTTR could cost less than 10% of the cost of otherwise required network reinforcement. RTTR is currently still a new technology; if it is widely adopted then economies of scale will drive this price down further.

There is an argument that by using variable technologies and accepting a level of risk, networks can deliver better value for money to consumers and system operators [34]. Network capacity is currently deterministic, and is provided through asset based redundancy; this is expensive and inefficient. If network capacity was subject to a cost-benefit analysis, technologies such as RTTR would compare favorably to the existing approach. This paper has demonstrated the benefit that RTTR can provide to network reliability. However changes in policy and standards may be required for before the full benefits can be unlocked.

C. Network Management and RTTR Deployment

The work presented in this paper has not accounted for the benefits of active network management informed by the RTTR. In reality it would be possible for network operators to embed RTTR into their Network Management System (NMS) [29] and use active control to minimize the probability of exceeding the RTTR.

When an outage occurs network operators take steps to reconfigure the remaining network such that customers remain connected. RTTR adds a powerful additional tool to this, as well as alleviating the need to reconfigure the network. The benefits of combining network reconfiguration and RTTR has been demonstrated by [35].

When deploying smart grids, the technology developers must be mindful of providing the correct information for system operators to make informed decisions. Too much information can cause decisions to become too complicated. In this case, the ideal information would be the rating of the determining span of each circuit, and information about the uncertainty of that value.

RTTR may not be an appropriate solution for all networks as many conductors will soon be in need of replacement. However, there are areas of network that are fit for purpose, but may need reinforcing before they would be replaced. These are the areas where RTTR, along with other smart grid technologies, could be successfully implemented. Further to this, there is no reason that RTTR could not be deployed on new networks; indeed networks could even be designed with RTTR in mind, possibly leading to a reduction in the number of conductors required [34].

VI. Conclusion

The primary contribution of this paper is a novel method for assessing the contribution of RTTR to power system reliability. Though current transmission and distribution systems are very reliable, if more load is connected the reliability rapidly degrades and corrective action must be taken. Conventionally new lines would be used to alleviate the risks and provide further reliability. However this paper shows how deploying RTTR could offset much of the risk without the need for any new infrastructure.

RTTR alone cannot deliver the high reliability the power systems currently operate under. However if it is deployed as part of a holistic smart grid strategy, network reliability could be maintained with a minimum of new conductors, instead relying on RTTR, DSR and energy storage to keep customers connected.

The analysis takes account of the reliability and uncertainty inherent in the use of RTTR. The uncertainty analysis suggests that for RTTR the greatest uncertainty arises from calculating the rating of components far from observation points. To offer the greatest benefit critical spans must be identified and instrumented, the whole network must be heavily instrumented or some means of predicting how ratings vary with distance must be devised and implemented.

Though this paper has demonstrated that RTTR can make a significant contribution to network reliability, it does not fit in to the existing paradigm of network design. Network design and planning standards must move away from asset based redundancy and accept the capacity provided by technologies such as RTTR. With proper planning and analysis, this will yield more cost-effective networks without compromising reliability.

References

[1] Engineering Reccomendation P27: Current Rating Guide for High Voltage Overhead Lines Operating in the UK Distribution System, Energy Networks Association, 1986.

[2] C.F. Price and R.R. Gibbon, "Statistical approach to thermal rating of overhead lines for power transmission and distribution," *IEE Proceedings C: Generation, Transmission and Distribution*, vol. 130, pp. 245-256, 1983.

[3] A. Michiorri, P.C. Taylor, S.C.E. Jupe and C.J. Berry, "Investigation into the influence of environmental conditions on power system ratings," *Proc. IMechE Part A: J. Power and Energy*, Vol 224 pp. 743-757, 2009.

[4] A. Michiorri, P.C. Taylor and S.C.E. Jupe, "Overhead line real-time rating estimation algorithm: description and validation," *IMechE Part A: J. Power and Energy*, Vol. 224, pp. 293-304, 2009.

[5] E. Cloet and J.L. Lilien, "Uprating Transmission Lines through the use of an innovative real-time monitoring system," in *12th Int. Conf. on Transmission and Distribution Construction, Operation and Live-Line Maintenance*, 2011, Providence, Rhode Island

[6] D.M. Greenwood, J.P. Gentle, K.S. Myers, P.J. Davison, I.J. West, J.W. Bush, G.L. Ingram and M.C.M. Troffaes., "A Comparison of Real-Time Thermal Rating Systems in the U.S. and the UK," *IEEE Trans. Power Delivery*, 2014.

[7] Department of Energy and Climate Change, *2050 Pathways* (2013, 18/07/2013).. Available: https://www.gov.uk/2050-pathways-analysis

[8] R. Billinton and R.N. Allan, "*Reliability evaluation of power systems*", Pitman Advanced Publishing Program, 1984.

[9] R.N. Allan, P. Djapic, and G. Strbac, "Assessing the Contribution of Distributed Generation to System Security," in *Int Conf. on Probabilistic Methods Applied to Power Systems*, 2006, Stockholm, Sweden.

[10] R. Billinton and L. Gan, "A Monte Carlo simulation model for adequacy assessment of multi-area generating systems," in *3rd Int.Conf. on Probabilistic Methods Applied to Power Systems* 1991, pp. 317-322.

[11] A. Sankarakrishnan and R. Billinton, "Sequential Monte Carlo simulation for composite power system reliability analysis with time varying loads," *IEEE Trans. Power Syst.*, vol. 10, pp. 1540-1545, 1995.

[12] R. Billinton, R. Karki, G. Yi, H. Dange, H. Po, and W. Wangdee, "Adequacy Assessment Considerations in Wind Integrated Power Systems," *IEEE Trans. Power Syst.*, vol. 27, pp. 2297-2305, 2012.

[13] W. Wangdee and R. Billinton, "Bulk electric system well-being analysis using sequential Monte Carlo simulation," *IEEE Trans. Power Syst.*, vol. 21, pp. 188-193, 2006.

[14] G. Celli, E. Ghiani, G. G. Soma, and F. Pilo, "Active distribution network reliability assessment with a pseudo sequential Monte Carlo method," in *IEEE PES PowerTech, Trondheim*, 2011.

[15] Y. Gao and R. Billinton, "Adequacy assessment of generating systems containing wind power considering wind speed correlation," *IET Renewable Power Generation*, vol. 3, pp. 217-226, 2009.

[16] R. Billinton, H. Chen, R. Ghajar, "Time-series models for reliability evaluation of power systems including wind energy," *Microelectronics Reliability*, vol. 36, pp. 1253-1261, 1996.

[17] H. Yu-Qing, P. Jian-Chun, S. Li, X. Chao and L. Jing-Jing, "Reliability evaluation of electrical distribution system considering the random energy output of wind power generators," in *2012 China Int. Conf. on Electricity Distribution*, 2012, Shanghai.

[18] J. He, Y. Sun, D.S. Kirschen, C. Singh, and L. Cheng, "State-space partitioning method for composite power system reliability assessment," *IET Generation, Transmission & Distribution*, vol. 4, pp. 780-792, 2010.

[19] Z. Kai, A.P. Agalgaonkar, K.M. Muttaqi, S. Perera, "Distribution System Planning With Incorporating DG Reactive Capability and System Uncertainties," *IEEE Trans. Sustainable Energy*, vol. 3, pp. 112-123, 2012.

[20] J. Mitra and X. Xufeng, "Composite system reliability analysis using particle swarm optimization," in *11th Int. Conf. on Probabilistic Methods Applied to Power System, 2010*, pp. 548-552, Singapore

[21] K. Moslehi and R. Kumar, "Smart Grid-a reliability perspective," in *Innovative Smart Grid Technologies*, 2010, Gothenburg, Sweden.

[22] L. Guo, C.X. Guo, W.H. Tang, and Q.H. Wu, "Evidence-based approach to power transmission risk assessment with component failure risk analysis," *IET Generation, Transmission & Distribution*, vol. 6, pp. 665-672, 2012.

[23] R. Billinton, R. Ghajar, F. Filippelli, and R. Del Bianco, "Transmission equipment reliability using the Canadian Electrical Association information system," in *Second Int. Conf. on the Reliability of Transmission and Distribution Equipment*, 1995, pp. 13-18.

[24] R. Billinton, S. Kumar, N. Chowdhury, K. Chu, K. Debnath, L. Goel, *et al.*, "A reliability test system for educational purposes-basic data," *IEEE Trans. Power Syst.*, vol. 4, pp. 1238-1244, 1989.

[25] Y. Yi, R.G. Harley, D. Divan, and T.G. Habetler, "Overhead conductor thermal dynamics identification by using Echo State Networks," in *Int. Joint Conf. on Neural Networks*, 2009, pp. 3436-3443.

[26] F. Miao, V. Vittal, G.T. Heydt, and R. Ayyanar, "Probabilistic Power Flow Studies for Transmission Systems With Photovoltaic Generation Using Cumulants," *IEEE Trans. Power Syst.*, vol. 27, pp. 2251-2261, 2012.

[27] CIGRÉ W.G. 22.12, "The thermal behaviour of overhead line conductors," *Electra*, vol. 114(3), pp. 107-25, 1992.

[28] G.H. Golub and C.F. Van Loan, *Matrix Computations*, Johns Hopkins University Press, 1996.

[29] S.C.E. Jupe, A.K. Kazerooni, and G. Murphy, "De-Risking the Implementation of Real-Time Thermal Ratings," in *22nd Int. Conf. on Electricity Distribution*, Stockholm, Sweden, 2013.

[30] P. Schell, B. Godard, H.M. Nguyen, and J.L. Lilien, "Using Dynamic Line Rating to minimize Curtailment of Wind power connected to rural power networks," in *11th Wind Integration Workshop*, Aarhus, Denmark, 2011.

[31] S. Abbott, S. Abdelkader, L. Bryans, and D. Flynn, "Experimental validation and comparison of IEEE and CIGRE dynamic line models," in *45th Int. Universities Power Engineering Conf.*,2010, Cardiff, Wales

[32] D.T.C. Wang, L.F. Ochoa, G.P. Harrison, "DG Impact on Investment Deferral: Network Planning and Security of Supply," *IEEE Trans.Power Syst.*, vol. 25, pp. 1134-1141, 2010.

[33] G. Murphy, "Implementation of Real-Time Thermal Ratings," Scottish Power Energy Networks, 2013, Available: http://www.spenergynetworks.co.uk/pages/dynamic_thermal_rating.asp

[34] G. Strbac, R. Moreno, D. Pudjianto, and M. Castro, "Towards a risk-based network operation and design standards," in *IEEE Power and Energy Society General Meeting*, 2011, Detroit, Michigan

[35] S.R. Blake, P.J. Davison, P.C. Taylor, D. Miller, A. Webster, "Use of Real-Time Thermal Ratings to Increase Network Reliability under Faulted Conditions," in *CIGRÉ Regional South-East European Conf.*, Sibiu, Romania, 2012.

David M. Greenwood (S'13) received his MEng in New and Renewable Energy from Durham University in 2010. He is currently undertaking a PhD at Newcastle University, investigating how to best exploit the Real-Time Thermal Rating of electrical conductors, and the associated benefits and challenges.

His previous work focused on the impact of weather and location on wind turbine failure rates.

Phil C. Taylor (SM'12) received an Engineering Doctorate in the field of intelligent demand side management techniques from the University of Manchester Institute of Science and Technology (UMIST) in 2001.

He joined Newcastle University in April 2013 when he was appointed Director of the Newcastle Institute for Research on Sustainability, Professor of Electrical Power Systems and tasked with overseeing the Science Central development. He previously held the DONG Energy Chair in Renewable Energy and was Deputy Director of the Durham Energy Institute and Director of the Multi-disciplinary Centre for Doctoral Training in Energy.